

Optimal Trade-Off for Succinct String Indexes

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Abstract. Let s be a string whose symbols are solely available through $\text{access}(i)$, a read-only operation that *probes* s and returns the symbol at position i in s . Many compressed data structures for strings, trees, and graphs, require two kinds of queries on s : $\text{select}(c, j)$, returning the position in s containing the j th occurrence of c , and $\text{rank}(c, p)$, counting how many occurrences of c are found in the first p positions of s . We give matching upper and lower bounds for this problem, improving the lower bounds given by Golynski [*Theor. Comput. Sci.* 387 (2007)] [PhD thesis] and the upper bounds of Barbay et al. [SODA 2007]. We also present new results in another model, improving on Barbay et al. [SODA 2007] and matching a lower bound of Golynski [SODA 2009]. The main contribution of this paper is to introduce a general technique for proving lower bounds on succinct data structures, that is based on the access patterns of the supported operations, abstracting from the particular operations at hand. For this, it may find application to other interesting problems on succinct data structures.

1 Introduction

We are given a read-only sequence $s \equiv s[0, n-1]$ of n symbols over an integer alphabet $\Sigma = [\sigma] \equiv \{0, 1, \dots, \sigma-1\}$, where $2 \leq \sigma \leq n$. The symbols in s can be read using $\text{access}(i)$, for $0 \leq i \leq n-1$: this primitive *probes* s and returns the symbol at position i , denoted by $s[i]$. Given the sequence s , its length n , and the alphabet size σ , we want to support the following query operations for a symbol $c \in \Sigma$:

- $\text{select}(c, j)$: return the position inside s containing the j th occurrence of symbol c , or -1 if that occurrence does not exist;
- $\text{rank}(c, p)$: count how many occurrences of c are found in $s[0, p-1]$.

We postulate that an auxiliary data structure, called a *succinct index*, is constructed in a preprocessing step to help answer these queries rapidly. In this paper, we study the natural and fundamental *time-space* tradeoff between two parameters t and r for this problem:

- t = the *probe complexity*, which is the maximal number of probes to s (i.e. calls to access) that the succinct index makes when answering a query³;

³ The time complexity of our results in the RAM model with logarithmic-sized words is linearly proportional to the probe complexity. Hence, we focus on the latter.

- r = the *redundancy*, which is the number of bits required by the succinct index, and does *not* include the space needed to represent s itself.

Clearly, these queries can be answered in negligible space but $O(n)$ probes by scanning s , or in zero probes by making a copy of s in auxiliary memory at preprocessing time, but with redundancy of $\Theta(n \log \sigma)$ bits. We are interested in succinct indices that use few probes, and have redundancy $o(n \log \sigma)$, i.e., asymptotically smaller than the space for s itself. Specifically, we obtain upper and lower bounds on the redundancy $r \equiv r(t, n, \sigma)$, viewed as a function of the maximum number t of probes, the length n of s , and the alphabet size σ . We assume that $t > 0$ in the rest of the paper.

Motivation. Succinct indices have numerous applications to problems involving indexing massive data sets [1]. The **rank** and **select** operations are basic primitives at the heart of many sophisticated indexing data structures for strings, trees, graphs, and sets [12]. Their efficiency is crucial to make these indexes fast and space-economical. Our results are most interesting for the case of “large” alphabets, where σ is a not-too-slowly growing function of n . Large alphabets are common in modern applications: e.g. many files are in Unicode character sets, where σ is of the order of hundreds or thousands. Inverted lists or documents in information retrieval systems can be seen as sequences s of words, where the alphabet Σ is obviously large and increasing with the size of the collection (it is the vocabulary of distinct words appearing over the entire document repository).

Our results. Our first contribution is showing that the redundancy r in bits

$$r(t, n, \sigma) = \Theta\left(\frac{n \log \sigma}{t}\right) \quad (1)$$

is tight for any succinct index solving our problem, for $t = O(\log \sigma / \log \log \sigma)$. (All the logarithms in this paper are to the base 2.) We provide matching upper and lower bounds for this range of values on t , under the assumption that $O(t)$ probes are allowed for **rank** and **select**, i.e. we ignore multiplicative constant factors. The result is composed by a lower bound of $r = \Omega(\frac{n \log \sigma}{t})$ bits that holds for $t = o(\log \sigma)$ and by an upper bound of $r = O(\frac{n \log \sigma}{t} + n \log \log \sigma)$. We also provide a lower bound of $r = \Omega(\frac{n \log t}{t})$ for $t = O(n)$, thus leaving open what the optimal redundancy when $t = \Omega(\frac{\log \sigma}{\log \log \sigma})$. Running times for the upper bound are $O(t + \log \log \sigma)$ for **rank** and $O(t)$ for **select**.

An interpretation of (1) is that, given a data collection D , if we want to build an additional succinct index on D that saves space by a factor t over that taken by D , we have to pay $\Omega(t)$ access cost for the supported queries. Note that the plain storage of the sequence s itself requires $n \log \sigma$ bits. Moreover, our result shows that it is suboptimal to build σ individual succinct indexes (like those for the binary-alphabet case, e.g. [19]), one per symbol $c \in [\sigma]$: the latter approach has redundancy $\Theta(\frac{\sigma n \log t}{t})$ while the optimal redundancy is given in eq. (1), when $t = O(\log \sigma / \log \log \sigma)$.

Lower bounds are our main findings, while the matching upper bounds are derived from known algorithmic techniques. Thus, our second contribution is a general technique that extends the algorithmic encoding/decoding approach in [5] in the sense that it abstracts from the specific query operation at hand, and focuses on its access pattern solely. For this, we can single out a sufficiently large, conflict free subset of the queries that are classified as *stumbling* or *z-unique*. In the former case, we extract direct knowledge from the *probed* locations; in the latter, the novelty of our approach is that we can extract (implicit) knowledge also from the *unprobed* locations. We are careful not to exploit the specific semantics of the query operations at this stage. As a result, our technique applies to other kinds of query operations for predecessor, prefix sum, permutation, and pattern searching problems, to name a few, as long as we can extract a sufficiently large subset of the queries with the aforementioned features. We will discuss them extensively in the full version.

We also provide further running times for the rank/select problem. For example, if $\sigma = (\log n)^{O(1)}$, the **rank** operation requires only $O(t)$ time; also, we can get $O(t \log \log \sigma \log^{(3)} \sigma)$ time⁴ for **rank** and $O(t \log \log \sigma)$ time for **select** (Theorem 5). We also have a lower bound of $r = \Omega(\frac{n \log t}{t})$ bits for the redundancy when $1 \leq t \leq n/2$, which leaves open what is the optimal redundancy when $t = \Omega(\log \sigma)$. As a corollary, we can obtain an entropy-compressed data structure that represents s using $nH_k(s) + O(\frac{n \log \sigma}{\log \log \sigma})$ bits, for any $k = o(\frac{\log_\sigma n}{\log \log \sigma})$, supporting **access** in $O(1)$ time, **rank** and **select** in $O(\log \log \sigma)$ time (here, $H_k(s)$ is the k th-order empirical entropy).

Related work. Succinct data structures are generally divided into two kinds, *systematic* and *non-systematic* [7]. Non-systematic data structures encode the input data and any auxiliary information together in a single representation, while systematic don't. The concept of succinct indexes applies to systematic ones; moreover, the concept of probes does not apply to non-systematic ones, since the input data is not distinguished from the index. In terms of time-space trade-off, our results extend the complexity gap between systematic and non-systematic succinct data structures (which was known for $\sigma = 2$) to any integer alphabet of size $\sigma \leq n$. This is easily seen by considering the case of $O(1)$ time/probes for **select**. Our systematic data structure requires $r = O(n \log \sigma)$ bits of redundancy whereas the non-systematic data structure of [12] uses just $O(n)$ bits of redundancy. However, if the latter should also provide $O(1)$ -time **access** to the encoded string, then its redundancy becomes $O(n \log \sigma)$. Note that eq. (1) is targeted for non-constant alphabet size σ whereas, for constant size, the lower and upper bounds for the $\sigma = 2$ case of [8] can be extended to obtain a matching bound of $\Omega(\frac{n \log t}{t})$ bits (see Appendix A.1).

The conceptual separation of the index from the input data was introduced to prove lower bounds in [7]. It was then explicitly employed for upper bounds in [6, 13, 20], and was fully formalized in [1]. The latter contains the best known up-

⁴ We define $\log^{(1)} x := \log_2 x$ and for integer $i \geq 2$, $\log^{(i)} x := \log_2(\log^{(i-1)} x)$.

per bounds for our problem⁵, i.e. $O(s)$ probes for **select** and $O(s \log k)$ probes for **rank**, for any two parameters $s \leq \log \sigma / \log \log \sigma$ and $k \leq \sigma$, with redundancy $O(n \log k + n(1/s + 1/k) \log \sigma)$. For example, fixing $s = k = \log \log \sigma$, they obtain $O(\log \log \sigma)$ probes for **select** and $O(\log \log \sigma \log^{(3)} \sigma)$ probes for **rank**, with redundancy $O(n \log \sigma / \log \log \sigma)$. By eq. (1), we get the same redundancy with $t = O(\log \log \sigma)$ probes for both **rank** and **select**. Hence, our probe complexity for **rank** is usually better than [1] while that of **select** is the same. Our $O(\log \log \sigma)$ running times are all better when compared to $O((\log \log \sigma)^2 \log^{(3)} \sigma)$ for **rank** and $O((\log \log \sigma)^2)$ for **select** in [1].

2 General Technique

This section aims at stating a general lower bound technique, of independent interest, which applies not only to both **rank** and **select** but to other query operations as well. Suppose we have a set S of strings of length n , and a set Q of queries that the must be supported on S using at most t probes each and an unknown amount r of redundancy bits. Under certain assumptions on S and Q , we can show a lower bound on r . Clearly, any choice of S and Q is allowed for the upper bound.

Terminology. We now give a framework that relies on a simple notion of entropy $H(S)$, where $H(X) = \lceil \log |X| \rceil$ for any class of $|X|$ combinatorial objects [4]. The framework extends the algorithmic encoding/decoding approach [5]. Consider an arbitrary algorithm \mathcal{A} that can answer to any query in Q performing at most t probes on any $s \in S$, using a succinct index with r bits. We describe how to encode s using \mathcal{A} and the succinct index as a black box, thus obtaining $E(s)$ bits of encoding. Then, we describe a decoder that knowing \mathcal{A} , the index of r bits, and the latter encoding of $E(s)$ bits, is able to reconstruct s in its original form. The encoding and decoding procedure are allowed unlimited (but finite) computing time, recalling that \mathcal{A} can make at most t probes per query.

The lower bound on r arises from the necessary condition $\max_{s \in S} E(s) + r \geq H(S)$, since otherwise the decoder cannot be correct. Namely, $r \geq H(S) - \max_s E(s)$: the lower $E(s)$, the tighter the lower bound for r . Our contribution is to give conditions on S and Q so that the above approach can hold for a variety of query operations, and is mostly oblivious of the specific operation at hand since the query access pattern to s is relevant. This appears to be novel.

First, we require S to be sufficiently dense, that is, $H(S) \geq n \log \sigma - \Theta(n)$. Second, Q must be a subset of $[\sigma] \times [n]$, so that the first parameter specifies a character c and the second one an integer p . Elements of Q are written as $q_{c,p}$. Third, answers to queries must be within $[n]$. The set Q must contain a number of stumbling or z -unique queries, as we define now. Consider an execution of \mathcal{A} on a query $q_{c,p} \in Q$ for a string s . The set of accessed position in s , expressed as a subset of $[n]$ is called an *access pattern*, and is denoted by $\text{Pat}_s(q_{c,p})$.

⁵ We compare ourselves with the improved bounds given in the full version of [1].

First, *stumbling* queries imply the occurrence of a certain symbol c inside their own access pattern: the position of c can be decoded by using just the answer and the parameters of the query. Formally, $q_{c,p} \in Q$ is stumbling if there exists a computable function f that takes in input c, p and the answer of $q_{c,p}$ over s , and outputs a position $x \in \text{Pat}_s(q_{c,p})$ such that $s[x] = c$. The position x is called the *target* of $q_{c,p}$. The rationale is that the encoder does not need to store any information regarding $s[x] = c$, since x can be extracted by the decoder from f and the at most t probed positions by \mathcal{A} . We denote by $Q'_s \subseteq Q$ the set of stumbling queries over s .

Second, z -*unique* queries are at the heart of our technique, where z is a positive integer. Informally, they have specific answers implying unique occurrences of a certain symbol c in a segment of s of length $z + 1$. Formally, a set U of answers is z -*unique* if for every query $q_{c,p}$ having answer in U , there exists a *unique* $i \in [p, p + z]$ such that $s[i] = c$ (i.e. $s[j] \neq c$ for all $j \in [p, p + z], j \neq i$). A query $q_{c,p}$ having answer in U is called z -unique and the corresponding position i is called the *target* of $q_{c,p}$. Note that, to our purposes, we will restrict to the cases where $H(U) = O(n)$. The rationale is the following: when the decoder wants to rebuild the string it must generate queries, execute them, and test whether they are z -unique by checking if their answers are in U . Once that happens, it can infer a position i such that $s[i] = c$, even though such a position is not probed by the query. We denote by $Q''_s(z) \subseteq Q \setminus Q'_s$ the set of z -unique queries over s that are *not* stumbling. We also let $\text{Tgt}_s(q_{c,p})$ denote the target of query $q_{c,p}$ over s , if it exists, and let $\text{Tgt}_s(Q) = \cup_{q \in Q} \text{Tgt}_s(q)$ for any set of queries Q .

Main statement. We now state our main theorem. Let S be a set of strings such that $H(S) \geq n \log \sigma - \Theta(n)$. Consider a set of queries Q that can be answered by performing at most t probes per query and using r bits of redundancy.

Theorem 1. *For any $z \in [\sigma]$, let $\lambda(z) = \min_{s \in S} |\text{Tgt}_s(Q'_s) \cup \text{Tgt}_s(Q''_s(z))|$. Then, there exists integers γ and δ with $\min\{\lambda(z), n\}/(15t) \leq \gamma + \delta \leq \lambda(z)$, such that any succinct index has redundancy*

$$r \geq \gamma \log \left(\frac{\sigma}{z} \right) + \delta \log \left(\frac{\sigma \delta}{t|Q|} \right) - \Theta(n)$$

The proof goes through a number of steps, each dealing with a different issue and is deferred to Section 3.

Applications. We now apply Theorem 1 to our two main problems, for an alphabet size $\sigma \leq n$.

Theorem 2. *Any algorithm solving rank queries on a string $s \in [\sigma]^n$ using at most $t = o(\log \sigma)$ character probes (i.e. access queries), requires a succinct index with $r = \Omega\left(\frac{n \log \sigma}{t}\right)$ bits of redundancy.*

Proof. We start by defining the set S of strings. For the sake of presentation, suppose σ divides n . An arbitrary string $s \in S$ is the concatenation of n/σ permutations of $[\sigma]$. Note that $|S| = (\sigma!)^{n/\sigma}$ and so we have $H(S) \geq n \log \sigma - \Theta(n)$ bits (by Stirling's approximation).

Without loss of generality, we prove the bound on a derivation of the **rank** problem. We define the set Q and fix the parameter $z = \sigma^{3/4}\sqrt{t}$, so that the queries are $q_{c,p} = \mathbf{rank}(c, p+z) - \mathbf{rank}(c, p)$, where $c \in [\sigma]$ and $p \in [n]$ with $p \bmod z \equiv 0$. In this setting, the z -unique answers are in $U = \{1\}$. Indeed, whenever $q_{c,p} = 1$, there exists just one instance of c in $s[p, p+z]$. Note that $|Q| = n\sigma/z > n$, for σ larger than some constant.

Observe that $\lambda(z) \geq n$, as each position i in s such that $s[i] = c$, is the target of exactly one query $q_{c,p}$: supposing the query is not stumbling, such a query is surely z -unique. By Theorem 1, $\gamma + \delta \geq n/(30t)$ since a single query is allowed to make up to $2t$ probes now. (This causes just a constant multiplicative factor in the lower bound.)

Having met all requirements, we apply Theorem 1, and get

$$r \geq \gamma \log\left(\frac{\sigma}{z}\right) - \delta \log\left(\frac{nt}{z\delta}\right) \quad (2)$$

We distinguish between two cases. If $\delta \leq n/\sigma^{1/4}$, then $\delta \log((nt)/(z\delta)) \leq \frac{n}{\sigma^{1/4}} \log\left(\frac{nt\sigma^{1/4}}{nz}\right) \leq \frac{n}{2\sigma^{1/4}} \log(t/\sigma)$, since $\delta \log(1/\delta)$ is monotone increasing in δ as long as $\delta \leq \lambda(z)/2$ (and $n/\sigma^{1/4} \leq \lambda(z)/2$ for sufficiently large σ). Hence, recalling that $t = o(\log \sigma)$, the absolute value of the second term on the right hand of (2) is $o(n/t)$ for σ larger than a constant. Moreover, $\gamma \geq n/(30t) - \delta \geq n/(60t)$ in this setting, so that the bound in (2) reduces to

$$r \geq \frac{n}{240t} \log \sigma - \frac{n}{120t} \log t - \Theta(n) = \frac{n}{240t} \log \sigma - \Theta(n).$$

In the other case, we have $\delta \geq n/\sigma^{1/4}$, and $\delta \log((nt)/(z\delta)) \leq \delta \log\left(\frac{\sigma^{1/4}t}{\sigma^{3/4}\sqrt{t}}\right) = \frac{\delta}{2} \log(t/\sigma)$. Therefore, we know in (2) that $\gamma \log(\sigma/z) + (\delta/2) \log(\sigma/t) \geq \frac{1}{2}(\gamma + \delta) \log(\sigma/z)$, as we chose $z \geq t$. Again, we obtain

$$r \geq \frac{n}{120t} \log \sigma - \Theta(n).$$

In both cases, the $\Theta(n)$ term is negligible as $t = o(\log \sigma)$, hence the bound. \square

Theorem 3. *Any algorithm solving **select** queries on a string $s \in [\sigma]^n$ using at most $t = o(\log \sigma)$ character probes (i.e. **access** queries), requires a succinct index with $r = \Omega\left(\frac{n \log \sigma}{t}\right)$ bits of redundancy.*

Proof. The set S of strings is composed by *full strings*, assuming that σ divides n . A full string contains each character exactly n/σ times and, differently from Theorem 2, has no restrictions on where they can be found. Again, we have $H(S) \geq n \log \sigma - \Theta(n)$.

The set Q of queries is $q_{c,p} = \mathbf{select}(c, p)$, where $p \in [n/\sigma]$, and all queries in Q are stumbling ones, as $\mathbf{select}(c, i) = x$ immediately implies that $s[x] = c$ (so f is the identity function). There are no z -unique queries here, so we can fix any value of z : we choose $z = 1$. It is immediate to see that $\lambda(z) = n$, and

$|Q| = n$, as there are only n/σ queries for each symbols in $[\sigma]$. By Theorem 1, we know that $\gamma + \delta \geq n/(15t)$. Hence, the bound is

$$r \geq \gamma \log \sigma + \delta \log\left(\frac{\sigma\delta}{nt}\right) \geq \frac{n}{15t} \log(\sigma/t^2) - \Theta(n).$$

Again, as $t = o(\log \sigma)$ the latter term is negligible and the bound follows. \square

3 Proof of Theorem 1

We give an upper bound on $E(s)$ for any $s \in S$ by describing an encoder and a decoder for s . In this way we can use the relation $\max_{s \in S} E(s) + r \geq H(S)$ to induce the claimed lower bound on r (see Section 2). We start by discussing how we can use z -unique and stumbling queries to encode a single position and its content compactly. Next, we will deal with conflicts between queries: not all queries in Q are useful for encoding. We describe a mechanical way to select a sufficiently large subset of Q so that conflicts are avoided. Bounds on γ and λ arise from such a process. To complete the encoding, we present how to store the parameters of the queries that the decoder must run.

Entropy of a single position and its content. We first evaluate the entropy of positions and their contents by exploiting the knowledge of z -unique and stumbling queries. We use the notation $H(S|\Omega)$ for some event Ω as a shortcut for $H(S')$ where $S' = \{s \in S | s \text{ satisfies } \Omega\}$.

Lemma 1. *For any $z \in [\sigma]$, let $\Omega_{c,p}$ be the condition “ $q_{c,p}$ is z -unique”. Then it holds $H(S) - H(S|\Omega_{c,p}) \geq \log(\sigma/z) - O(1)$.*

Proof. Note that set $(S|\Omega_{c,p}) = \{s \in S : \text{Tgt}_s(q_{c,p}) \text{ is defined on } s\}$ for a given query $q_{c,p}$. It is $|(S|\Omega_{c,p})| \leq (z+1)\sigma^{n-1}$ since there at most $z+1$ candidate target cells compatible with $\Omega_{c,p}$ and at most $|S|/\sigma$ possible strings with position containing c at a fixed position. So, $H(S|\Omega_{c,p}) \leq \log(z+1) + H(S) - \log \sigma$, hence the bound. \square

Lemma 2. *Let $\Omega'_{c,p}$ be the condition “ $q_{c,p}$ is a stumbling query”. Then, it holds that $H(S) - H(S|\Omega'_{c,p}) \geq \log(\sigma/t) - O(1)$.*

Proof. The proof for this situation is already known from [9]. In our notation, the proof goes along the same lines as that of Lemma 1, except that we have t choices instead of $z+1$. To see that, let m_1, m_2, \dots, m_t be the positions, in temporal order, probed by the algorithm \mathcal{A} on s while answering $q_{c,p}$. Since the query is stumbling, the target will be one of m_1, \dots, m_t . It suffices to remember which one of the t steps probe that target, since their values m_1, \dots, m_t are deterministically characterized given \mathcal{A} , s , $q_{c,p}$. \square

Conflict handling. In general, multiple instances of Lemma 1 and/or Lemma 2 cannot be applied independently. We introduce the notion of conflict on the targets and show how to circumvent this difficulty. Two queries $q_{b,o}$ and $q_{c,p}$

conflict on s if at least one of the following three condition holds: (i) $\text{Tgt}_s(q_{c,p}) \in \text{Pat}_s(q_{b,o})$, (ii) $\text{Tgt}_s(q_{b,o}) \in \text{Pat}_s(q_{c,p})$, (iii) $\text{Tgt}_s(q_{c,p}) = \text{Tgt}_s(q_{b,o})$. A set of queries where no one conflicts with another is called *conflict free*. The next lemma is similar to the one found in [10], but the context is different.

Lemma 3 defines a lower bound on the maximum size of a conflict free subset of Q . We use an iterative procedure that maintains at each i th step a set Q_i^* of conflict free queries and a set C_i of available targets, such that no query q whose target is in C_i will conflict with any query $q' \in Q_{i-1}^*$. Initially, C_0 contains all targets for the string s , so that by definition $|C_0| \geq \lambda(z)$. Also, Q_0^* is the empty set.

Lemma 3. *Let $i \geq 1$ be an arbitrary step and assume $|C_{i-1}| > 2|C_0|/3$. Then, there exists Q_i^* and C_i such that (a) $|Q_i^*| = 1 + |Q_{i-1}^*|$, (b) Q_i^* is conflict free, (c) $|C_i| \geq |C_0| - 5it \geq \lambda(z) - 5it$.*

Proof. We first prove that there exists $u \in C_{i-1}$ such that no more than $3t$ queries probe u . Assume by contradiction that for any u , at least $3t$ queries probe u . Then, we would collect $3t|C_{i-1}| > 2|C_0|t$ probes in total. However, any query can probe at most t cells, summing up to $|C_0|t$, giving a contradiction. At step i , we choose u as a target, say, of query $q_{c,p}$ for some c, p . This maintains invariant (a) as $Q_i^* = Q_{i-1}^* \cup \{q_{c,p}\}$. As for invariant (b), we remove the potentially conflicting targets from C_{i-1} , and produce C_i . Let $I_u \subseteq C_{i-1}$ be the set of targets for queries probing u over s , where by the above properties $|I_u| \leq 3t$. We remove u and the elements in I_u and $\text{Pat}_s(q_{c,p})$. So, $|C_i| = |C_{i-1}| - |\{u\}| - |I_u| - |\text{Pat}_s(q_{c,p})| \geq |C_{i-1}| - 1 - 3t - t \geq |C_0| - 5it$. \square

By applying Lemma 3 until $|C_i| \leq 2|C_0|/3$, we obtain a final set Q^* , hence the following:

Corollary 1. *For any $s \in S$, $z \in [\sigma]$, there exists a set Q^* containing z -unique and stumbling queries of size $\gamma + \delta \geq \min\{\lambda(z), n\}/(15t)$, where $\gamma = |\{q \in Q^* | q \text{ is stumbling on } s\}|$ and $\delta = |\{q \in Q^* | q \text{ is } z\text{-unique on } s\}|$.*

Encoding. We are left with the main task of describing the encoder. Ideally, we would like to encode the targets, each with a cost as stated in Lemma 1 and Lemma 2, for the conflict free set Q^* mentioned in Corollary 1. Characters in the remaining positions can be encoded naively as a string. This approach has a drawback. While encoding which queries in Q are stumbling has a payoff when compared to Lemma 2, we don't have such a guarantee for z -unique queries when compared to Lemma 1. Without getting into details, according to the choice of the parameters $|Q|$, z and t , such encoding sometimes saves space and sometimes does not: it may use even more space than $H(S)$. For example, when $|Q| = O(n)$, even the naive approach works and yields an effective lower bound. Instead, if Q is much larger, savings are not guaranteed. The main point here is that we want to overcome such a dependence on the parameters and always guarantee a saving, which we obtain by means of an implicit encoding of z -unique queries. Some machinery is necessary to achieve this goal.

Archetype and trace. Instead of trying to directly encode the information of Q^* as discussed above, we find a query set Q^A called the *archetype* of Q^* , that is indistinguishable from Q^* in terms of γ and δ . The extra property of Q^A is to be decodable using just $O(n)$ additional bits, hence $E(s)$ is smaller when Q^A is employed. The other side of the coin is that our solution requires a two-step encoding. We need to introduce the concept of *trace* of a query $q_{c,p}$ over s , denoted by $\text{Trace}_s(q_{c,p})$. Given the access pattern $\text{Pat}_s(q_{c,p}) = \{m_1 < m_2 < \dots < m_t\}$ (see Section 2), the trace is defined as the string $\text{Trace}_s(q_{c,p}) = s[m_1] \cdot s[m_2] \cdot \dots \cdot s[m_t]$. We also extend the concept to sets of queries, so that for $\hat{Q} \subseteq Q$, we have $\text{Pat}_s(\hat{Q}) = \bigcup_{q \in \hat{Q}} \text{Pat}_s(q)$, and $\text{Trace}_s(\hat{Q})$ is defined using the sorted positions in $\text{Pat}_s(\hat{Q})$.

Then, we define a *canonical ordering* between query sets. We define the predicate $q_{c,p} \prec q_{d,g}$ iff $p < g$ or $p = g \wedge c < d$ over queries, so that we can sort queries inside a single query set. Let $Q_1 = \{q_1 \prec q_2 \prec \dots \prec q_x\}$ and let $Q_2 = \{q'_1 \prec q'_2 \prec \dots \prec q'_y\}$ be two distinct query sets. We say that $Q_1 \prec Q_2$ iff either $q_1 \prec q'_1$ or recursively $(Q_1 \setminus \{q_1\}) \prec (Q_2 \setminus \{q'_1\})$.

Given Q^* , its archetype Q^A obeys to the following conditions for the given s :

- it is conflict free and has the same number of queries of Q^* ;
- it contains exactly the same stumbling queries of Q^* , and all remaining queries are z -unique (note that they may differ from those in Q^*);
- if p_1, p_2, \dots, p_x are the positional arguments of queries in Q^* , then the same positions are found in Q^A (while character c_1, c_2, \dots, c_x may change);
- $\text{Pat}_s(Q^*) = \text{Pat}_s(Q^A)$;
- among those query sets complying with the above properties, it is the minimal w.r.t. to the canonical ordering \prec .

Note that Q^* complies with all the conditions above but the last. Therefore, the archetype of Q^* always exists, being either a smaller query set (w.r.t. to \prec) or Q^* itself. The encoder can compute Q^A by exhaustive search, since its time complexity is not relevant to the lower bound.

First step: encoding for trace and stumbling queries. As noted above the stumbling queries for Q^* and Q^A are the same, and there are δ of them. Here, we encode the trace together with the set of stumbling queries. The rationale is that the decoder must be able to rebuild the original trace only, whilst encoding of the positions which are not probed is left to the next step, together with z -unique queries. Here is the list of objects to be encoded in order:

- (a) The set of stumbling queries expressed as a subset of Q .
- (b) The access pattern $\text{Pat}_s(Q^A)$ encoded as a subset of $[n]$, the positions of s .
- (c) The *reduced* trace, obtained from $\text{Trace}_s(Q^A)$ by removing all the characters in positions that are targets of stumbling queries. Encoding is performed naively by storing each character using $\log \sigma$ bits. The positions thus removed, relatively to the trace, are stored as a subset of $[\|\text{Trace}_s(Q^A)\|]$.
- (d) For each stumbling query $q_{c,p}$, in the canonical order, an encoded integer i of $\log t$ bits indicating that the i th probe accesses the target of the query.

The decoder starts with an empty string, it reads the access pattern in (b), the set of removed positions in (c), and distributes the contents of the reduced trace (c) into the remaining positions. In order to fill the gaps in (c), it recovers the stumbling queries in (a) and runs each of them, in canonical ordering. Using the information in (d), as proved by Lemma 2, it can discover the target in which to place its symbol c . Since Q^A is conflict free, we are guaranteed that each query will always find a symbol in the probed positions.

Lemma 4. *Let ℓ be the length of $\text{Trace}_s(Q^A)$. The first step encodes information (a)–(d) using at most $\ell \log \sigma + O(n) + \delta \log(|Q|/\delta) - \delta \log(\sigma/t)$ bits.*

Proof. Space occupancy for all objects: (a) uses $\log \binom{|Q|}{\delta} = \delta \log(|Q|/\delta) + O(\delta)$; (b) uses $\log \binom{n}{\ell} \leq n$ bits; (c) uses $(\ell - \delta) \log \sigma$ bits for the reduced trace plus at most ℓ bits for the removed positions; (d) uses $\delta \log t$ bits. \square

Second step: encoding of z -unique queries and unprobed positions. We now proceed to the second step, where targets for z -unique queries are encoded along with the unprobed positions. They can be rebuilt using queries in Q^A . To this end, we assume that encoding of Lemma 4 has already been performed and, during decoding, we assume that the trace has been already rebuilt. Recall that γ is the number of z -unique queries. Here is the list of objects to be encoded:

- (e) The set of queries in Q^A that are z -unique, expressed as a subset of Q^A according to the canonical ordering \prec . Also the set of z -unique answers U is encoded as a subset of $[n]$.
- (f) For each z -unique query $q_{c,p}$, in canonical order, the encoded integer p . This gives a multiset of γ integers in $[n]$.
- (g) The *reduced* unprobed region of the string, obtained by removing all the characters in positions that are targets of z -unique queries. Encoding is performed naively by storing each character using $\log \sigma$ bits. The positions thus removed, relatively to the unprobed region, are stored as a subset of $[n - \ell]$.
- (h) For each z -unique query $q_{c,p}$, in the canonical order, an encoded integer i of $\log z + O(1)$ bits indicating which position in $[p, p + z]$ contains c .

The decoder first obtains Q^A by exhaustive search. It initializes a set of $|Q^A|$ empty couples (c, p) representing the arguments of each query in canonical order. It reads (e) and reuses (a) to obtain the parameters of the stumbling queries inside Q^A . It then reads (f) and fills all the positional arguments of the queries. Then, it starts enumerating all query sets in canonical order that are compatible with the arguments known so far. That is, it generates characters for the arguments of z -unique queries, since the rest is known. Each query set is then tested in the following way. The decoder executes each query by means of the trace. If the execution tries a probe outside the access pattern, the decoder skips to the next query set. If the query conflicts with any other query inside the same query set, the decoder skips. If the query answer denotes that the query is not z -unique (see Section 2 and (e)), it skips. In this way, all the requirements for the archetype are met, hence the first query set that is not skipped is Q^A .

Using Q^A the decoder rebuilds the characters in the missing positions of the reduced unprobed region: it starts by reading positions in (g) and using them to distribute the characters in the reduced region encoded by (g) again. For each z -unique query $q_{c,p} \in Q^A$, in canonical order, the decoder reads the corresponding integer i inside (h) and infers that $s[i+p] = c$. Again, conflict freedom ensures that all queries can be executed and the process can terminate successfully. Now, the string s is rebuilt.

Lemma 5. *The second step encodes information $(e)-(h)$ using at most $(n - \ell) \log \sigma + O(n) - \gamma \log(\sigma/z)$ bits.*

Proof. Space occupancy: (e) uses $\log \binom{|Q^A|}{\gamma} \leq |Q^A|$ bits for the subset plus, recalling from Section 2, $O(n)$ bits for U ; (f) uses $\log \binom{n+\gamma}{\gamma} \leq 2n$ bits; (g) requires $(n - \ell - \gamma) \log \sigma$ bits for the reduced unprobed region plus $\log \binom{n-\ell}{\gamma}$ bits for the positions removed; (h) uses $\gamma \log z + O(\gamma)$ bits. \square

Proof (of Theorem 1). By combining Lemma 4 and Lemma 5 we obtain that for each $s \in S$, $E(s) \leq n \log \sigma + O(n) + \delta \log \left(\frac{t|Q|}{\delta \sigma} \right) - \gamma \log \left(\frac{\sigma}{z} \right)$. We know that $r + \max_{s \in S} E(s) \geq H(S) \geq n \log \sigma - \Theta(n)$, hence the bound follows. \square

4 Upper bounds

Our approach follows substantially the one in [1], but uses two new ingredients, that of *monotone* hashing [3] and *succinct SB-trees* [14], to achieve an improved (and in many cases optimal) result. We first consider these problems in a slightly different framework and give some preliminaries.

Preliminaries. We are given a subset $T \subseteq [\sigma]$, where $|T| = m$. Let $R(i) = |\{j \in T \mid j < i\}|$ for any $i \in [\sigma]$, and $S(i)$ be the $i + 1$ st element of T , for any $i \in [m]$.

The value of $S(R(p))$ for any p is named the *predecessor* of p inside T . For any subset $T \subseteq [\sigma]$, given access to $S(\cdot)$, a *succinct SB-tree* [14] is a systematic data structure that supports predecessor queries on T , using $O(|T| \log \log \sigma)$ extra bits. For any $c > 0$ such that $|T| = O(\log^c \sigma)$, the succinct SB-tree supports predecessor queries in $O(c)$ time plus $O(c)$ calls to $S(\cdot)$. The data structure relies on a precomputed table of $n^{1-\Omega(1)}$ bits depending only on σ , not on T .

A *monotone minimal perfect* hash function for T is a function h_T such that $h_T(x) = R(x)$ for all $x \in T$, but $h_T(x)$ can be arbitrary if $x \notin T$. We need the following result:

Theorem 4 ([3]). *There is a monotone minimal perfect hash function for T that:*

- occupies $O(m \log \log \sigma)$ bits and can be evaluated in $O(1)$ time;
- occupies $O(m \log^{(3)} \sigma)$ bits and can be evaluated in $O(\log \log \sigma)$ time.

Although function $R(\cdot)$ has been studied extensively in the case that T is given explicitly, we consider the situation where T can only be accessed through (expensive) calls to $S(\cdot)$. We also wish to minimize the space used (so e.g. creating an explicit copy of T in a preprocessing stage, and then applying existing solutions, is ruled out). We give the following extension of known results:

Lemma 6. *Let $T \subseteq [\sigma]$ and $|T| = m$. Then, for any $1 \leq k \leq \log \log \sigma$, there is a data structure that supports $R(\cdot)$ in $O(\log \log \sigma)$ time plus $O(1 + \log k)$ calls to $S(\cdot)$, and uses $O((m/k) \log \log \sigma)$ bits of space. The data structure uses a pre-computed table (independent of T) of size $\sigma^{1-\Omega(1)}$ bits.*

Proof. We construct the data structure as follows. We store every $(\log \sigma)$ th element of T in a y-fast trie [22]. This divides T into *buckets* of $\log \sigma$ consecutive elements. For any bucket B , we store every k th element of T in a succinct SB-tree. The space usage of the y-fast trie is $O(m)$ bits, and that of the succinct SB-tree is $O((m/k) \log \log \sigma)$ bits.

To support $R(\cdot)$, we first perform a query on the y-fast trie, which takes $O(\log \log \sigma)$ time. We then perform a query in the appropriate bucket, which takes $O(1)$ time by looking up a pre-computed table (which is independent of T) of size $\sigma^{1-\Omega(1)}$. The query in the bucket also requires $O(1)$ calls to $S(\cdot)$. We have so far computed the answer within k keys in T : to complete the query for $R(\cdot)$ we perform binary search on these k keys using $O(\log k)$ calls to $S(\cdot)$.

Supporting rank and select. In what follows, we use Lemma 6 choosing $k = 1$ and $k = \log \log \sigma$. We now show the following result, contributing to eq. (1). Note that the first option in Theorem 5 has optimal index size for t probes, for $t \leq \log \sigma / \log \log \sigma$. The second option has optimal index size for t probes, for $t \leq \log \sigma / \log^{(3)} \sigma$, but only for **select**.

Theorem 5. *For any $1 \leq t \leq \sigma$, there exist data structures with the following complexities:*

- (a) **select** in $O(t)$ probes and $O(t)$ time, and **rank** in $O(t)$ probes and $O(t + \log \log \sigma)$ time using a succinct index with $r = O(n(\log \log \sigma + (\log \sigma)/t))$ bits of redundancy. If $\sigma = (\log n)^{O(1)}$, the **rank** operation requires only $O(t)$ time.
- (b) **select** in $O(t)$ probes and $O(t \log \log \sigma)$ time, and **rank** in $O(t \log^{(3)} \sigma)$ probes and $O(t \log \log \sigma \log^{(3)} \sigma)$ time, using $r = O(n(\log^{(3)} \sigma + (\log \sigma)/t))$ bits of redundancy for the succinct index.

Proof. We divide the given string s into contiguous blocks of size σ (assume for simplicity that σ divides $n = |s|$). As in [1, 12], we use $O(n)$ bits of space, and incur an additive $O(1)$ -time slowdown, to reduce the problem of supporting **rank** and **select** on s to the problem of supporting these operations on a given block B . We denote the individual characters of B by $B[0], \dots, B[\sigma - 1]$.

Our next step is also as in [1]: letting n_c denote the multiplicity of character c in B , we store the bitstring $Z = 1^{n_0}01^{n_1}0 \dots 1^{n_{\sigma-1}}0$, which is of length 2σ ,

and augment it with the binary **rank** and **select** operations, using $O(\sigma)$ bits in all. Let $c = B[i]$ for some $0 \leq i \leq \sigma - 1$, and let $\pi[i]$ be the position of c in a stably sorted ordering of the characters of B (π is a permutation). As in [1], **select**(c, \cdot) is reduced, via Z , to determining $\pi^{-1}(j)$ for some j . As shown in [16], for any $1 \leq t \leq \sigma$, permutation π can be augmented with $O(\sigma + (\sigma \log \sigma)/t)$ bits so that $\pi^{-1}(j)$ can be computed in $O(t)$ time plus t evaluations of $\pi(\cdot)$ for various arguments.

If T_c denotes the set of indexes in B containing the character c , we store a minimal monotone hash function h_{T_c} on T_c , for all $c \in [\sigma]$. To compute $\pi(i)$, we probe s to find $c = B[i]$, and observe that $\pi(i) = R(i) + \sum_{i=0}^{c-1} n_i$. The latter term is obtained in $O(1)$ time by **rank** and **select** operations on Z , and the former term by evaluating $h_{T_c}(i)$. By Theorem 4, the complexity of **select**(c, i) is as claimed.

As noted above, supporting **rank**(c, i) on s reduces to supporting **rank** on an individual block B . If T_c is as above, we apply Lemma 6 to each T_c , once with $k = 1$ and once with $k = \log \log \sigma$. Lemma 6 requires some calls to $S(\cdot)$, but this is just **select**(c, \cdot) restricted to B , and is solved as described above. If $\sigma = (\log n)^{O(1)}$, then $|T_c| = (\log n)^{O(1)}$, and we store T_c itself in the succinct SB-tree, which allows us to compute $R(\cdot)$ in $O(1)$ time using a (global, shared) lookup table of size $n^{1-\Omega(1)}$ bits. \square

The enhancements described here also lead to more efficient non-systematic data structures. Namely, for $\sigma = \Theta(n^\varepsilon)$, $0 < \varepsilon < 1$, we match the lower bound of [10, Theorem 4.3]. Moreover, we improve asymptotically both in terms of space and time over the results of [1]:

Corollary 2. *There exists a data structure that represents any string s of length n using $nH_k(s) + O(\frac{n \log \sigma}{\log \log \sigma})$ bits, for any $k = o(\frac{\log_\sigma n}{\log \log \sigma})$, supporting access in $O(1)$ time, **rank** and **select** in $O(\log \log \sigma)$ time.*

Proof. We take the data structure of Theorem 5(a), where $r = O(\frac{n \log \sigma}{\log \log \sigma})$. We compress s using the high-order entropy encoder of [6, 13, 20] resulting in an occupancy of $nH_k(s) + a$ bits, where $H_k(s)$ is the k th-order empirical entropy and a is the extra space introduced by encoding. We have $a = O(\frac{n}{\log_\sigma n}(k \log \sigma + \log \log n))$, which is $O(\frac{n \log \sigma}{\log \log \sigma})$ for our choice of k , hence it doesn't dominate on the data structure redundancy. Operation **access** is immediately provided in $O(1)$ time by the encoded structure, thus the time complexity of Theorem 5 applies. \square

References

1. J. Barbay, M. He, J. I. Munro, and S. S. Rao. Succinct indexes for strings, binary relations and multi-labeled trees. *SODA 2007*, 680–689, 2007. Also, full version available in Internet.
2. P. Beame and F.E. Fich. Optimal bounds for the predecessor problem and related problems. *J. Comput. Syst. Sci.*, 65:38–72, 2002.

3. D. Belazzougui, P. Boldi, R. Pagh, and S. Vigna. Monotone minimal perfect hashing: searching a sorted table with $O(1)$ accesses. *SODA 2009*, 785–794, 2009.
4. T. M. Cover and J. A. Thomas. *Elements of Information Theory* (Wiley Series in Telecommunications and Signal Processing), Wiley-Interscience 2006.
5. E. D. Demaine and A. López-Ortiz. A linear lower bound on index size for text retrieval. *J. Algorithms*, 48(1):2–15, 2003.
6. P. Ferragina and R. Venturini. A simple storage scheme for strings achieving entropy bounds. *Theor. Comput. Sci.*, 372(1):115–121, 2007.
7. A. Gál and P. Bro Miltersen. The cell probe complexity of succinct data structures. *Theor. Comput. Sci.*, 379:405–417, 2007.
8. A. Golynski. Optimal lower bounds for rank and select indexes. *TCS*, 387:348–359, 2007.
9. A. Golynski. *Upper and Lower Bounds for Text Indexing Data Structures*. PhD Th., U. Waterloo 2007.
10. A. Golynski. Cell probe lower bounds for succinct data structures. *SODA 2009*, 625–632, 2009.
11. A. Golynski, R. Grossi, A. Gupta, R. Raman, and S. S. Rao. On the size of succinct indices. In *Proc 15th ESA, LNCS 4698*, pages 371–382, 2007.
12. A. Golynski, J. I. Munro, and S. S. Rao. Rank/select operations on large alphabets: a tool for text indexing. In *Proc. of the 17th ACM-SIAM SODA*, pages 368–373, 2006.
13. R. González and G. Navarro. Statistical encoding of succinct data structures. *CPM 2006*, 294–305, 2006.
14. R. Grossi, A. Orlandi, R. Raman, and S. S. Rao. More haste, less waste: Lowering the redundancy in fully indexable dictionaries. *STACS 2009*, 517–528, 2009.
15. P. B. Miltersen. Lower bounds on the size of selection and rank indexes. *SODA 2005*, 11–12, 2005.
16. J. I. Munro, R. Raman, V. Raman, and S. S. Rao. Succinct representations of permutations. In *Proc. 30th ICALP, LNCS 2719*, pages 345–356, 2003.
17. M. Pătraşcu. Succincter. In *Proc. 49th IEEE FOCS*, pages 305–313, 2008.
18. M. Pătraşcu and M. Thorup. Time-space trade-offs for predecessor search. *STOC 2006*, 232–240, 2006.
19. R. Raman, V. Raman, and S. S. Rao. Succinct indexable dictionaries, with applications to representing k -ary trees, prefix sums and multisets. *ACM Transactions on Algorithms*, 4, 2007.
20. K. Sadakane and R. Grossi. Squeezing succinct data structures into entropy bounds. In *Proc. of the 17th ACM-SIAM SODA*, pages 1230–1239, 2006.
21. P. van Emde Boas. Design and implementation of an efficient priority queue. *Math. Syst. Theory*, 10:99–127, 1977.
22. Dan E. Willard. Log-logarithmic worst-case range queries are possible in space $\Theta(N)$. *IPL*, 17(2):81–84, 1983.

A Appendix

A.1 Extending previous work

In this section, we prove a first lower bound for **rank** and **select** operations. We extend the existing techniques of [8], originally targeted at $\sigma = 2$. The bound has the advantage to hold for any $1 \leq t \leq n/2$, but it is weaker than eq. (1) when $\log t = o(\log \sigma)$.

Theorem 6. *Let s be an arbitrary string of length n over the alphabet $\Sigma = [\sigma]$, where $\sigma \leq n$. Any algorithm solving **rank** or **select** queries on s using at most t character probes (i.e. **access** queries), where $1 \leq t \leq n/2$, requires a succinct index with $r = \Omega\left(\frac{n \log t}{t}\right)$ bits of redundancy.*

Intuitively speaking, the technique is as follows: it first creates a set of queries the data structure must answer and then partitions the string into classes, driven by the algorithm behaviour. A bound on the entropy of each class gives the bound. However, our technique proves that finding a set of queries adaptively for each string can give an higher bound for $t = o(\log \sigma)$.

Before getting into the full details we prove a technical lemma that is based on the concept of *distribution* of characters in a string: Given a string T of length u over alphabet ϕ , the distribution (vector) \mathbf{d} for u over ϕ is a vector in \mathbb{N}^ϕ containing the frequency of each character in T . We can state:

Lemma 7. *For any $\phi \geq 2$, $u \geq \phi$ and distribution \mathbf{d} for u on ϕ , it holds*

$$\max_{\mathbf{d}} \binom{u}{\mathbf{d}_1 \mathbf{d}_2 \dots \mathbf{d}_\phi} = \frac{u!}{\left(\frac{u}{\phi}\right)!^\phi} \leq \phi^u \left(\frac{\phi}{u}\right)^{\phi/2} \sqrt{\phi}.$$

Proof. The maximization follows from the concavity of the multinomial function and the uniqueness of its maximum: the maximum is located at the uniform distribution $\mathbf{d} = (u/\phi, u/\phi, \dots, u/\phi)$. The upper bound arises from double Stirling inequality, as we have:

$$\begin{aligned} \frac{u!}{\left(\frac{u}{\phi}\right)!^\phi} &\leq \frac{\sqrt{2\pi} u^{u+1/2} e^{-u+\frac{1}{12u}}}{(\sqrt{2\pi})^\phi (u/\phi)^{u+\phi/2} e^{-u+\frac{\phi}{12(u/\phi)+12}}} \\ &\leq (2\pi)^{(1-\phi)/2} u^{u+1/2} \left(\frac{\phi}{u}\right)^{u+1/2+(\phi-1)/2} \\ &= O(2^{(1-\phi)/2}) \phi^u \phi^{1/2} \left(\frac{\phi}{u}\right)^{(\phi-1)/2} \end{aligned}$$

and the lemma follows.

Let $L = 3\sigma t$ and assume for sake of simplicity that L divides n . We start by defining the query set

$$\mathcal{Q} = \{\text{select}(c, 3ti) | c \in [\sigma] \wedge i \in [n/L]\}$$

having size $\gamma = \frac{n\sigma}{L} = \frac{n}{3t}$. The set of strings on which we operate, S , is designed so that all queries in \mathcal{Q} return a position in the set. We build strings by concatenating n/L *chunks*, each of which is generated in all possible ways. A single chunk is built by aligning $3t$ occurrences of each symbol in $[\sigma]$ and then permuting the resulting substring of length L in any possible way.

A *choices* tree for \mathcal{Q} is a composition of smaller decision trees. At the top, we build the full binary tree of height r , each leaf representing a possible choices for the index bits values. For each leaf of r , we append the decision tree of our algorithm for the first query \mathcal{Q}_1 on every possible string conditioned on the choice of the index. The decision tree has height at most t and each node has fan-out σ , being all possible results of probing a location of the string. Each node is labeled with the location the algorithm chooses to analyze, however we are not interested in this information. The decision tree has now $2^r \sigma^t$ leaves. At each leaf we append the decision tree for the second query \mathcal{Q}_2 , increasing the number of leaves again, and so on up to \mathcal{Q}_γ . Without loss of generality we will assume that all decision trees have height exactly t and that each location is probed only once (otherwise we simply remove double probes and add some padding ones in the end). Leaves at the end of the whole decision tree are assigned strings from S which are *compatible* with the root-to-leaf path: each path defines a set of answers A for all γ queries and a string is said to be compatible with a leaf if the answers to \mathcal{Q} on that string is exactly A and all probes during the path match the path. For any leaf x , we will denote the amount of compatible strings by $C(x)$. Note that the tree partitions the entire set of strings, i.e. $\sum_{x \text{ is a leaf}} C(x) = |S|$. Our objective is to prove that $C(x)$ cannot be too big, and so prove that to distinguish all the answer sets the topmost tree must have at least some minimum height. More in detail, we will first compute C^* , an upper bound on $C(x)$ for any x , and then use the following relation to obtain the bound:

$$\log |S| = \log \sum_{x \text{ is a leaf}} C(x) \leq \log(\# \text{ of leaves}) + \log C^* \leq r + t\gamma \log \sigma + \log C^* \quad (3)$$

Before continuing, we define some notation. For any path, the number of *probed* locations is $t\gamma = n/3$, while the number of *unprobed* locations is denoted by U . We divide a generic string in some leaf x into consecutive *blocks* of characters defined depending on the answer set to \mathcal{Q} for that leaf, as follows. The set $S_i \in \mathcal{Q}$ of σ of queries is defined as $S_i = \mathcal{Q} \cap \{(c, x) \in [n] \times [\sigma] \mid x = i\}$; we define the block B_i as the interval $[\min_c A_x(S_i), (\min_c A_x(S_{i+1})) - 1]$ (where A_x defines the answer to a set of queries), i.e. the maximum span covered by answer set to S_i in some leaf x . Note that the partitioning in blocks is dependant only on \mathcal{Q} , i.e. it is typical of a leaf and not of a specific string, and that due to our particular choice of S , the length $|B_i|$ is exactly L . Thus, the number of blocks is n/L .

We now associate a conceptual value u_i to each block, which represents the number of *unprobed* characters in that block, so that $\sum_{i=1}^{n/L} u_i = U$. As in a leaf of the choices tree all probed locations have the same values, the only degree of freedom distinguishing compatible strings between themselves lies in the unprobed locations. We will compute C^* by analyzing single blocks, and we will

focus on the right side of the following:

$$\frac{C^*}{\sigma^U} = c_1^* c_2^* \cdots c_{n/L}^* = \frac{g_1}{\sigma^{u_1}} \frac{g_2}{\sigma^{u_2}} \frac{g_3}{\sigma^{u_3}} \cdots \frac{g_{n/L}}{\sigma^{u_{n/L}}} \quad (4)$$

where $g_i \leq \sigma^{u_i}$ represents the possible assignment of unprobed characters for block i and c_i^* the ratio g_i/σ^{u_i} .

We categorize blocks into two classes: *determined* blocks, having $u_i < \sigma t$ and the remaining *undetermined* ones. For determined ones, we will assume $g_i = \sigma^{u_i}$. For the remaining ones we upper bound the possible choices by their maximum value, i.e. we employ Lemma 7 to bound their entropy. Joining it with $u_i > \sigma t$ we obtain:

$$c_i^* \leq \frac{\sigma^{1/2} \sigma^{u_i} \left(\frac{\sigma}{u_i}\right)^{\sigma/2}}{\sigma^{u_i}} \leq \sigma^{1/2} \left(\frac{1}{t}\right)^{\sigma/2}$$

The last step involves finding the number of such determined and undetermined blocks. As the number of global probes is at most $t\gamma = n/3$, the maximum number of determined blocks (where the number of probed locations is $L - u_i > 2\sigma t$) is $(t\gamma)/(2\sigma t) = n/(2L)$. The number of undetermined blocks is then at least $n/L - n/(2L) = n/(2L)$. Recalling that our upper bound increases with the number of determined blocks, we keep it to the minimum. Therefore, we have:

$$\log C^* \leq U \log \sigma + \frac{n}{2L} \frac{\sigma}{2} \log \left(\frac{1}{t}\right) + \frac{n}{2L} \frac{1}{2} \log \sigma = \Theta \left(\frac{n}{t} \log \left(\frac{1}{t}\right) \right) \quad (5)$$

Joining Equation 5, 3 and the fact that $t\gamma + U = n$, we obtain that

$$n \log \sigma - \frac{n}{L} = \log |S| \leq r + t\gamma \log \sigma + U \log \sigma - \Theta \left(\frac{n}{t} \log t \right)$$

and the bound follows.

We can prove an identical result for operation **rank**. The set S of hard strings is the set of all strings of length n over σ . We conceptually divide the strings in blocks of $L = 3\sigma t$ consecutive positions, starting at 0. With this in mind, we define the set of queries

$$\mathcal{Q} = \{\mathbf{rank}(c, iL) | c \in [\sigma] \wedge i \in [n/L]\},$$

i.e. we ask for the distribution of the whole alphabet every L characters, resulting in a batch of $\gamma = \frac{n}{3t}$ queries. The calculations are then parallel to the previous case. \square